08_sentiment_forecasting_models

December 2, 2025

1 Sentiment-Augmented Forecasting

Use the combined modeling dataset to compare baseline PP models vs sentiment-augmented models. We run rolling-origin tests, compute metrics, and inspect coefficients to quantify the incremental value of OPEC sentiment.

[1]:
```
from pathlib import Path
import sys
import warnings

import pandas as pd
import matplotlib.pyplot as plt
from IPython.display import display

NOTEBOOK_DIR = Path(__file__).resolve().parent if "__file__" in globals() else␣
  ↪Path.cwd()
ROOT = NOTEBOOK_DIR.parent
if str(ROOT) not in sys.path:
    sys.path.append(str(ROOT))

from src.model_dataset_utils import build_modeling_dataset
from src.sentiment_model_utils import (
    define_model_specs,
    run_models_backtest,
    compute_forecast_metrics,
    extract_coefficients,
    plot_forecast_vs_actual,
    plot_forecast_errors,
    plot_coefficients,
)

DATA = ROOT / "data"
ART = ROOT / "artifacts"
PLOTS = ROOT / "plots"
for path in (ART, PLOTS):
    path.mkdir(parents=True, exist_ok=True)

warnings.filterwarnings("ignore")
```

```python
pd.set_option("display.max_columns", 50)
print(f"ROOT set to {ROOT}")
```

```
ROOT set to c:\PythonProjects\LLM-polypropylene
```

[2]:

```python
df_model = pd.DataFrame()

artifact_path = ART / "modeling_dataset_monthly.csv"
if artifact_path.exists():
    df_model = pd.read_csv(artifact_path, parse_dates=["date"])
    df_model = df_model.set_index("date").sort_index()
    print(f"Loaded modeling dataset from {artifact_path}")
else:
    print("Modeling dataset artifact missing; rebuilding in memory via␣
 ↪build_modeling_dataset().")
    df_model, _ = build_modeling_dataset(ROOT)

if df_model.empty:
    print("Modeling dataset is empty; please run notebooks 02, 06, 07 first.")
else:
    print(f"Shape: {df_model.shape}")
    print(f"Date range: {df_model.index.min().date()} to {df_model.index.max().
 ↪date()}")
    print(f"Columns: {list(df_model.columns)}")
    display(df_model.head())
    display(df_model.tail())
```

```
Loaded modeling dataset from c:\PythonProjects\LLM-
polypropylene\artifacts\modeling_dataset_monthly.csv
Shape: (130, 16)
Date range: 2015-02-28 to 2025-11-30
Columns: ['PP', 'PGP', 'CRUDE', 'ret_PP', 'ret_PGP', 'ret_CRUDE', 'resid_PP',
'score_demand', 'score_overall', 'score_price_outlook', 'score_supply',
'index_demand', 'index_overall', 'index_price_outlook', 'index_supply',
'index_hybrid']
```

date	PP	PGP	CRUDE	ret_PP	ret_PGP	ret_CRUDE
2015-02-28	8748.0	8748.0	50.724736	0.054348	0.054348	0.069364
2015-03-31	8829.4	8829.4	47.854091	0.009262	0.009262	-0.058257
2015-04-30	9348.0	9348.0	54.628096	0.057075	0.057075	0.132392
2015-05-31	9142.0	9142.0	59.372000	-0.022283	-0.022283	0.083274
2015-06-30	8786.0	8786.0	59.828637	-0.039720	-0.039720	0.007662

date	resid_PP	score_demand	score_overall	score_price_outlook
2015-02-28	NaN	NaN	NaN	NaN
2015-03-31	NaN	NaN	NaN	NaN
2015-04-30	NaN	NaN	NaN	NaN

```
2015-05-31 -0.025787          NaN          NaN                NaN
2015-06-30 -0.033245          NaN          NaN                NaN

            score_supply  index_demand  index_overall  index_price_outlook  \
date
2015-02-28           NaN           NaN            NaN                  NaN
2015-03-31           NaN           NaN            NaN                  NaN
2015-04-30           NaN           NaN            NaN                  NaN
2015-05-31           NaN           NaN            NaN                  NaN
2015-06-30           NaN           NaN            NaN                  NaN

            index_supply  index_hybrid
date
2015-02-28           NaN           NaN
2015-03-31           NaN           NaN
2015-04-30           NaN           NaN
2015-05-31           NaN           NaN
2015-06-30           NaN           NaN
            PP  PGP  CRUDE  ret_PP  ret_PGP  ret_CRUDE  resid_PP  \
date
2025-07-31 NaN  NaN    NaN     NaN      NaN        NaN       NaN
2025-08-31 NaN  NaN    NaN     NaN      NaN        NaN       NaN
2025-09-30 NaN  NaN    NaN     NaN      NaN        NaN       NaN
2025-10-31 NaN  NaN    NaN     NaN      NaN        NaN       NaN
2025-11-30 NaN  NaN    NaN     NaN      NaN        NaN       NaN

            score_demand  score_overall  score_price_outlook  score_supply  \
date
2025-07-31     -0.465910            0.7             0.730664     -0.382759
2025-08-31     -0.439590            0.7             0.341918     -0.376988
2025-09-30     -0.592581            0.3             0.675067     -0.389453
2025-10-31     -0.494205            0.4             0.173203     -0.468063
2025-11-30     -0.406237            0.3            -0.027499     -0.509039

            index_demand  index_overall  index_price_outlook  index_supply  \
date
2025-07-31    -13.950573            8.3            33.377305      5.704018
2025-08-31    -14.390164            9.0            33.719222      5.327030
2025-09-30    -14.982745            9.3            34.394289      4.937577
2025-10-31    -15.476949            9.7            34.567492      4.469514
2025-11-30    -15.883186           10.0            34.539993      3.960475

            index_hybrid
date
2025-07-31      8.357687
2025-08-31      8.414022
2025-09-30      8.412280
```

```
2025-10-31      8.315014
2025-11-30      8.154320
```

[3]:
```python
if df_model.empty:
    print("No data to define model specs.")
else:
    specs = define_model_specs(df_model)
    if not specs:
        print("No model specs could be defined (missing necessary columns).")
    else:
        for s in specs:
            print(f"Model {s.name}: target={s.target}, regressors={s.
 ↪regressors}, target_lags={s.target_lags}, reg_lags={s.reg_lags}")
```

```
Model A_baseline: target=resid_PP, regressors=['ret_CRUDE', 'ret_PGP'],
target_lags=[1], reg_lags={'ret_CRUDE': [1], 'ret_PGP': [1]}
Model B_sentiment_hybrid: target=resid_PP, regressors=['ret_CRUDE', 'ret_PGP',
'index_hybrid'], target_lags=[1], reg_lags={'ret_CRUDE': [1], 'ret_PGP': [1],
'index_hybrid': [0, 1]}
Model C_sentiment_sections: target=resid_PP, regressors=['ret_CRUDE', 'ret_PGP',
'index_hybrid', 'index_demand', 'index_supply', 'index_price_outlook'],
target_lags=[1], reg_lags={'ret_CRUDE': [1], 'ret_PGP': [1], 'index_hybrid': [0,
1], 'index_demand': [0, 1], 'index_supply': [0, 1], 'index_price_outlook': [0,
1]}
```

[4]:
```python
backtest_df = pd.DataFrame()

if df_model.empty:
    print("Skipping backtest; dataset is empty.")
elif not specs:
    print("Skipping backtest; no model specs.")
else:
    TEST_MONTHS = 24
    MIN_TRAIN = 36
    backtest_df = run_models_backtest(df_model, specs,␣
 ↪test_size_months=TEST_MONTHS, min_train_months=MIN_TRAIN)
    if backtest_df.empty:
        print("Backtest produced no results; check data length or specs.")
    else:
        print(f"Backtest rows: {len(backtest_df)}, models:␣
 ↪{backtest_df['model_name'].nunique()}")
        display(backtest_df.head())
        out_path = ART / "sentiment_backtest_results.csv"
        backtest_df.to_csv(out_path, index=False)
        print(f"Saved backtest results -> {out_path}")
```

```
Backtest rows: 72, models: 3
```

date	y_true	y_pred	model_name	train_end

```
0 2023-04-30 -0.014802 -0.005182  A_baseline 2023-03-31
1 2023-05-31 -0.053684 -0.002118  A_baseline 2023-04-30
2 2023-06-30  0.000785 -0.013949  A_baseline 2023-05-31
3 2023-07-31  0.016094 -0.000106  A_baseline 2023-06-30
4 2023-08-31  0.049295  0.005123  A_baseline 2023-07-31
```

```
Saved backtest results -> c:\PythonProjects\LLM-
polypropylene\artifacts\sentiment_backtest_results.csv
```

[5]:
```python
metrics_df = pd.DataFrame()
if backtest_df.empty:
    print("Skipping metrics; no backtest results.")
else:
    metrics_df = compute_forecast_metrics(backtest_df)
    display(metrics_df)
    metrics_path = ART / "sentiment_model_metrics.csv"
    metrics_df.to_csv(metrics_path, index=False)
    print(f"Saved metrics -> {metrics_path}")
```

```
             model_name   N       MAE      RMSE      MAPE  \
0            A_baseline  24  0.015783  0.020950  0.735172
1    B_sentiment_hybrid  24  0.018708  0.022892  0.558053
2  C_sentiment_sections  24  0.029359  0.034768 -0.083298

   Directional_Accuracy
0              0.458333
1              0.375000
2              0.375000
```

```
Saved metrics -> c:\PythonProjects\LLM-
polypropylene\artifacts\sentiment_model_metrics.csv
```

[6]:
```python
coefs_df = pd.DataFrame()
if df_model.empty or not specs:
    print("Skipping coefficient extraction; missing data/specs.")
else:
    coefs_df = extract_coefficients(df_model, specs)
    display(coefs_df.head())
    coefs_path = ART / "sentiment_model_coefficients.csv"
    coefs_df.to_csv(coefs_path, index=False)
    print(f"Saved coefficients -> {coefs_path}")
```

```
           model_name        variable  coefficient
0          A_baseline    resid_PP_lag1    -0.227014
1          A_baseline  ret_CRUDE_lag1    -0.029404
2          A_baseline     ret_PGP_lag1     0.454791
3          A_baseline        intercept     0.001219
4  B_sentiment_hybrid    resid_PP_lag1     0.269924
```

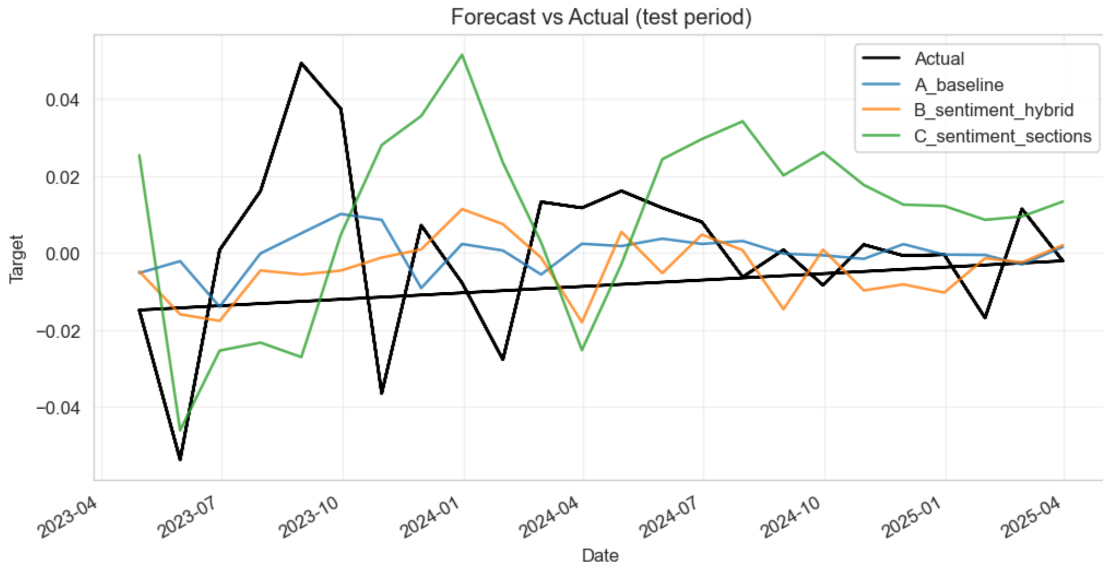
```
Saved coefficients -> c:\PythonProjects\LLM-
```

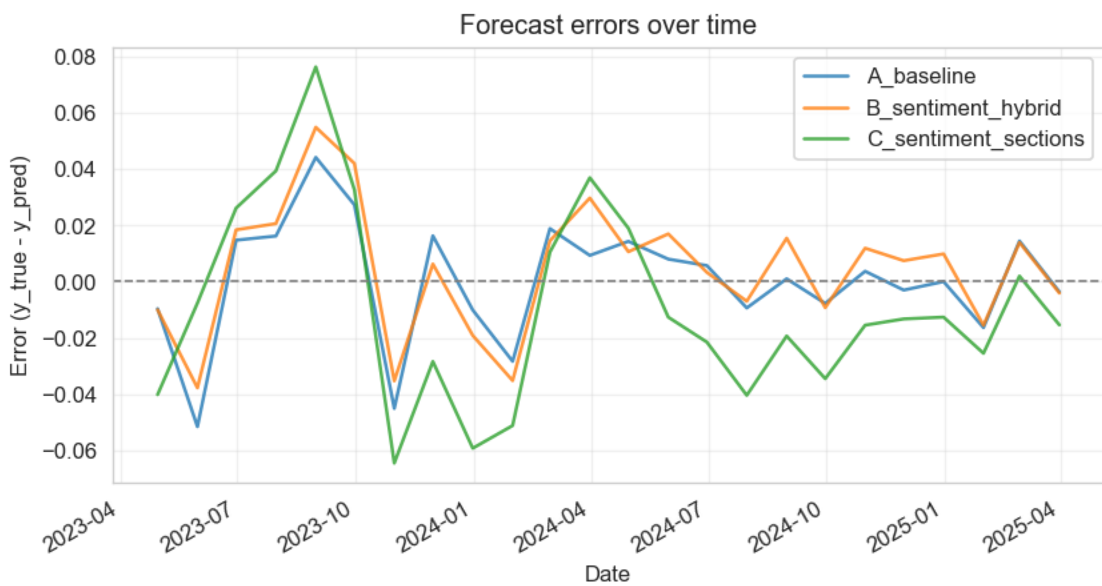
```
polypropylene\artifacts\sentiment_model_coefficients.csv
```

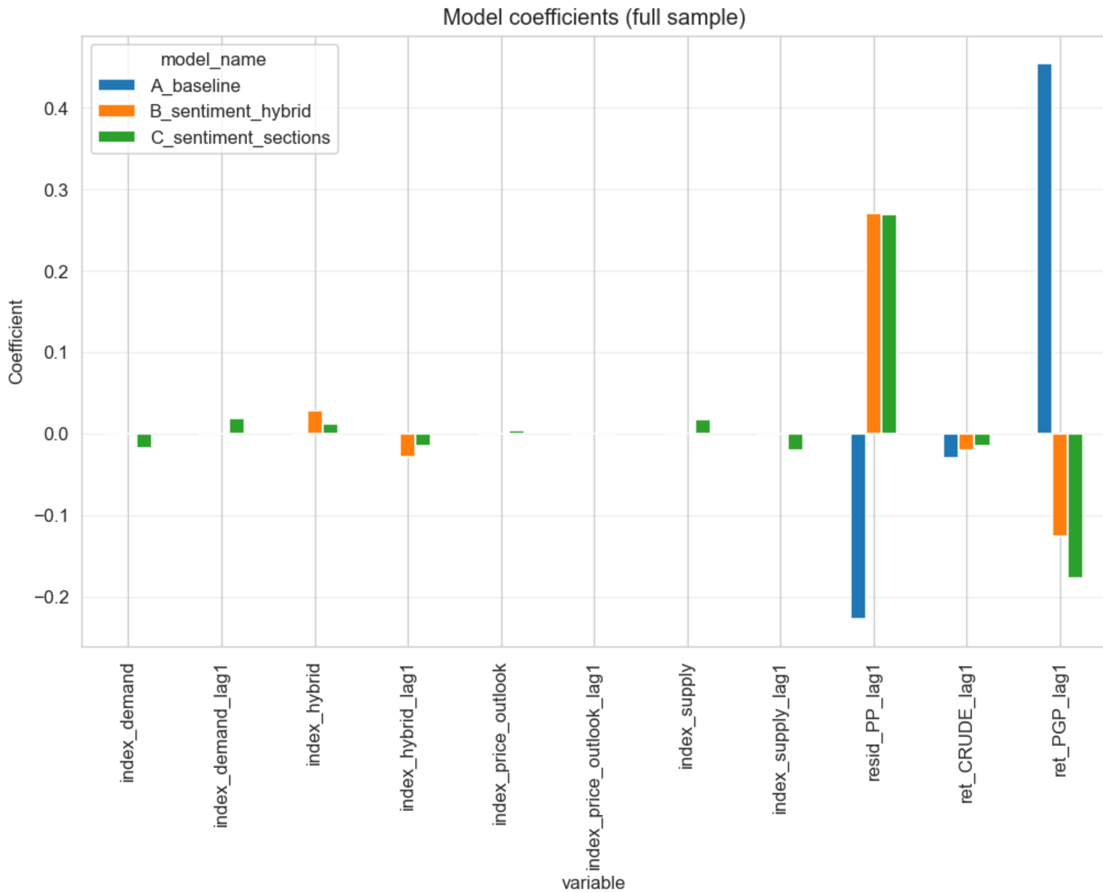
[7]:
```python
if backtest_df.empty:
    print("Skipping plots; no backtest results.")
else:
    try:
        fig1 = plot_forecast_vs_actual(backtest_df)
        path1 = PLOTS / "forecast_vs_actual_baseline_vs_sentiment.png"
        fig1.savefig(path1, dpi=150, bbox_inches="tight")
        display(fig1)
    except Exception as exc:
        print(f"Forecast vs actual plot failed: {exc}")
    finally:
        plt.close('all')

    try:
        fig2 = plot_forecast_errors(backtest_df)
        path2 = PLOTS / "forecast_errors_baseline_vs_sentiment.png"
        fig2.savefig(path2, dpi=150, bbox_inches="tight")
        display(fig2)
    except Exception as exc:
        print(f"Forecast errors plot failed: {exc}")
    finally:
        plt.close('all')

    if not coefs_df.empty:
        try:
            fig3 = plot_coefficients(coefs_df)
            path3 = PLOTS / "sentiment_model_coefficients.png"
            fig3.savefig(path3, dpi=150, bbox_inches="tight")
            display(fig3)
        except Exception as exc:
            print(f"Coefficient plot failed: {exc}")
        finally:
            plt.close('all')
```


Forecast vs Actual (test period)
Actual
A_baseline
B_sentiment_hybrid
C_sentiment_sections
0.04
0.02
0.00
−0.02
−0.04
Target
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date


Forecast errors over time
A_baseline
B_sentiment_hybrid
C_sentiment_sections
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
Error (y_true - y_pred)
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
2024-10
2025-01
2025-04
Date



[8]:
```
if metrics_df is None or metrics_df.empty:
    print("No metrics to interpret.")
else:
    best = metrics_df.sort_values('RMSE').iloc[0]
    print(f"Best model by RMSE: {best['model_name']} (RMSE={best['RMSE']:.4f},␣
↪MAE={best['MAE']:.4f})")
    if 'A_baseline' in metrics_df['model_name'].values:
        base_rmse = metrics_df.loc[metrics_df['model_name']=='A_baseline',␣
↪'RMSE'].iloc[0]
        if base_rmse > 0:
            improvement = (base_rmse - best['RMSE']) / base_rmse
            print(f"Improvement vs baseline: {improvement*100:.1f}%")
    print("Use these results to discuss whether sentiment adds forecasting␣
↪value.")
```

```
Best model by RMSE: A_baseline (RMSE=0.0209, MAE=0.0158)
Improvement vs baseline: 0.0%
Use these results to discuss whether sentiment adds forecasting value.
```